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Multi-Attribute Procurement Auctions in the Presence of Satisfaction Risk

He Huang
School of Economics and Business Administration, Chongqing University, Chongqing 400044, China, huanghe@cqu.edu.cn

Liming Liu
Faculty of Business, Lingnan University, Hong Kong, China, limingliu@ln.edu.hk

Geoffrey Parker
Thayer School of Engineering, Dartmouth College, Hanover, New Hampshire 03755, USA, geoffrey.g.parker@dartmouth.edu

Yinliang (Ricky) Tan
A. B. Freeman School of Business, Tulane University, New Orleans, Louisiana 70118, USA, ytan2@tulane.edu

Hongyan Xu*
School of Economics and Business Administration, Chongqing University, Chongqing 400044, China, xuhongyan@cqu.edu.cn

Procurement auctions are widely used by governments and corporations to solicit bids for services and projects. Such auctions involve significant risk for the buyer, because the delivered quality is highly uncertain. We examine a multi-attribute procurement auction combined with a performance-based contract. In this setting, suppliers submit bids which include both price and promised quality. After the buyer awards the contract to the winning bidder with the highest score, the supplier exerts efforts to accomplish the project, and buyer satisfaction is randomly affected by both promised quality and effort. A performance-contingent reward or penalty occurs upon project delivery. We show that bidders jointly optimize promised quality and effort before submitting a bid price. Depending upon the relative impacts from promised quality and effort on buyer's satisfaction, the promised quality and execution effort can be complements or substitutes. Our analysis reveals that the information rent that the supplier gains depends on the relationship between promised quality and buyer satisfaction. Further, the optimal scoring rule distorts promised quality downwardly. We find that either reserve quality or price alone is insufficient to exclude undesirable bidders. Compared with efficient mechanism, the effort under optimal mechanism is distorted upwardly (downwardly) when it substitutes (complements) promised quality. We also find that the risk uncertainty can benefit both buyer and supplier, under certain conditions of an additive relationship between supplier's behaviors and randomness, resulting in a Pareto improvement.

Key words: procurement auctions; performance-based contracts; satisfaction risk; mechanism design
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1. Introduction

Procurement auctions are widely adopted to solicit suppliers (i.e., bidders) of unique products, such as services, construction projects, and public infrastructure. This type of auction is also known as a "reverse auction," since the roles of buyers and suppliers are reversed. Many corporations and governments have used procurement auctions to induce competition in order to reduce procurement costs and cycle time. It has been estimated that the use of procurement auctions is increasing at a rate of 10–15% per year (Beall et al. 2003). With the development of information technology, firms and governments are increasingly embracing multi-attribute procurement auctions to obtain services in areas such as marketing, insurance, legal services, human resources, maintenance, and consulting (Elmaghraby 2007). It is estimated that procurement auctions account for 7% of total U.S. government contracts worth roughly $31.2 billion per year (Ladick 2015). Honeywell has been reported to use procurement auctions to procure legal services, even for litigation (Edwards 2015). Recently, Indian Railways announced plans to implement procurement auctions with the aim of saving $1.4 billion in spending per year (Ians 2018).

Unlike sales auctions in which bids usually only involve price, bids in procurement auctions also include bidders' promise to deliver certain quality levels as well. This unique aspect creates multidimensional bids in this class of procurement auctions. Further, the uncertainty in buyer (dis)satisfaction also plays a significant role in procurement auctions. The *ex ante* uncertainty regarding satisfaction is governed by two endogenous decisions from the supplier's side: the promised quality and their unobservable effort during the project. Note that the "satisfaction risk" will only be realized after the service (or product) is delivered. As a consequence, the issue of satisfaction risk becomes imperative during the design of service procurement auctions. On the one hand, satisfaction is directly influenced by the promised quality of the winning supplier during the multidimensional auction. On the other hand, the supplier's effort also influences the final quality realized. Buyer satisfaction is commonly conceptualized as a function of the difference between proposed and delivered quality. Thus, the existence of satisfaction risk poses a critical research question: What is the best mechanism to overcome the problem of procuring multi-attribute services or goods when satisfaction risk is present?

In this study, we investigate the role of the satisfaction risk in the context of performance-based contracts (PBCs). PBCs have been widely adopted in operations management practice (Tan et al. 2017). For example, the construction industry has long suffered from low productivity, and PBCs are one of the most common mechanisms to mitigate satisfaction risk (Groves 2017). According to *Forbes* (Vitasek 2015), the U.S. Department of Transportation is moving toward a national performance-based approach. Transportation authorities in Canada, Finland, and New Zealand have already adopted scoring auctions combined with PBCs for road management and maintenance projects (Stankevich et al. 2005). For example, the New South Wales, Victoria, and Queensland road authorities in Australia applied a quality-based selection (QBS) method to select the winning bid during bidder evaluation and selection. QBS considers quality and price, and awards the contract to the bidder with the highest overall score. Then, during the project execution phase, payments for on-road works are made at a unit rate, and payments for off-road works are performance-based and paid on a lump-sum basis. Penalties are included in PBCs to address user dissatisfaction, e.g., 500 USD/day/pothole for potholes > 2.5 cm (Stankevich et al. 2005). Beyond infrastructure spending, PBCs are also widely applied in industrial settings to control the risk of moral hazard where, *ex ante*, quality is uncertain. For example, in the aerospace industry, the number of normal flying hours (a key measure of product utilization and reliability) is usually uncertain. Rolls-Royce, a major aircraft engine manufacturer, is recognized as a pioneer in the application of PBCs to mitigate customer risk from the key quality measure. Under PBCs, airlines agree to pay an extra fee to Rolls-Royce proportional to actual flying hours (Guajardo et al. 2012). Essentially, many quality performance indicators, such as completion time, soundness of surface drainage systems, and prompt response to emergencies, must be specified and included in the bid; however, their realization is uncertain. In these scenarios, both the buyer and the supplier share a common understanding of the eventual satisfaction assessment, which is usually based on the difference between the promised quality and actual delivery performance. In addition to promised quality and effort, another important factor contributing to satisfaction risk is environmental uncertainty, which is beyond the control of the supplier. The effects of different uncertainties on bidder behaviors, revenue, buyer utility, and mechanism design are crucial research issues from both practical and theoretical perspectives, and provide the motivation for our study.

The analysis of bidder behaviors and mechanism design in the procurement auctions described above has significant practical implications. However, the presence of a buyer's uncertain satisfaction in multi-attribute auction is not extensively studied in the existing literature (e.g., Asker and Cantillon 2008, Branco 1997, Che 1993, Parkes and Kalagnanam 2005). To the best of our knowledge, the model discussed in this study is the first attempt to embed endogenous satisfaction risk into multi-attribute scoring auctions. The crucial feature that distinguishes our work from previous studies is that we examine both effort and promised quality can simultaneously affect the degree of uncertain satisfaction, and the buyer and suppliers have *ex ante* information asymmetry, where previous studies usually model a one-dimensional supplier decision with regard to effort (e.g., Baker 1992, Kim et al. 2007, Laffont and Tirole 1987, McAfee and McMillan 1987). Thus, the present study combines multi-attribute auction with PBC, where moral hazard interacts with observable bidding tools in an environment that involves *ex ante* competition and subsequent risk.

Our analysis provides several important managerial implications. First, we find that the supplier in the auction with satisfaction risk must optimize promised quality and effort together, while price can be determined separately. This is an extension of the previous literature on multi-attribute auctions without buyer satisfaction rewards and penalties, which shows that supplier quality and price can be determined separately (Che 1993). Also, we note that satisfaction risk can drive bidders to bid less (or more) aggressively on the quality dimension depending on the effect of promised quality on satisfaction, thus reducing or increasing the supplier's information rent. Second, our analysis highlights the importance of classifying the relationship between promised quality and effort (in particular, whether they are complements or substitutes) and how they influence the supplier's behavior. We find that less effort will be exerted in an optimal auction (i.e., buyer utility maximization) than in an efficient auction (i.e., social surplus maximization) when effort complements promised quality, while the opposite is true when effort substitutes for promised quality. Third, with respect to mechanism design, we find that an optimal reserve score is required to avoid a situation where undesirable bidders leave the buyer with a loss. A crucial implication here is that neither reserve quality nor reserve price alone is sufficient to exclude undesirable bidders that can create negative buyer surplus. Finally, to further explore the impact of uncertainty on our results, we analyze two classes of satisfaction functions (linear and nonlinear) under an additive relationship between bidders' behaviors and randomness. Interestingly, we find that uncertainty can actually benefit both supplier and buyer under certain conditions, resulting in a Pareto improvement.

The rest of the study is organized as follows. We first review the relevant literature and position of our study with respect to it in section 2. The model and analysis of bidder behavior are presented in section 3. In section 4, we explore the mechanism designs for efficient and optimal auctions of the buyer. Section 5 investigates the impacts of uncertainty. In section 6, we consider two extensions of our base model. Finally, in section 7, we conclude our study with key takeaways and directions for future research.

2. Literature Review

The current work is closely related to three streams of literature: scoring auctions, keyword auctions, and procurement auctions or procurement risks in supply chain management. We review the existing studies in each stream and point out the differences between the current work and previous works to highlight our contributions.

2.1. Scoring Auctions

Che (1993) proposed the quasi-linear scoring rule used to design efficient and optimal procurement auctions (multidimensional or multi-attribute auctions) and compared buyer utilities under different auction mechanisms. Bushnell and Oren (1994) and Branco (1997) also used scoring rules to handle bidding in multidimensional auctions with non-price dimensions. Beil and Wein (2002) as well as Parkes and Kalagnanam (2005) applied scoring rules in iterative auctions. Asker and Cantillon (2008) studied scoring auctions in which suppliers have multidimensional private information and found that, like one-dimensional cases, quality bidding in optimal auctions is distorted downward compared with efficient auctions. Our study considers the *ex ante* risk given uncertain buyer satisfaction in a multi-attribute procurement auction associated with moral hazard (supplier effort), and finds that effort can be distorted either downward or upward in the optimal mechanism.

Chen et al. (2010b) used scoring auctions to regulate project bidding with failure risk, assuming that suppliers bid based on both project cost and the penalties in the event of failure, and that the binary probability of success is exogenous. In the current study, both promised quality in bid and effort affect satisfaction risk, and supplier effort is incentivized by a contingent transfer. Gupta et al. (2015a) studied the bidder's behavior and agency decisions in A+B auction of construction projects, which do not focus on optimal auction design due to the assumption of a linear scoring rule. Our study is different in that it explores scoring auctions with moral hazard and analyzes the impact from different types of uncertainty on supplier bidding behavior, hidden effort, and scoring rule. In essence, the contingent transfers in the previous two papers referenced above and our model resemble the payment in a PBC, which concerns the quality or outcome of service provision and ties contractor payment to achieved performance. In the literature, PBCs are used to solve the moral hazard problem described in agency theory (e.g., Baker 1992, Holmstrom 1979, Kim et al. 2007). In particular, Laffont and Tirole (1987) and McAfee and McMillan (1987) studied the linear PBC with a direct auction mechanism, where suppliers simply decide their levels of effort and report their types accordingly. In the model presented here, which is an indirect multidimensional auction, the suppliers decide promised quality, price, and effort, and thus a contingent payment scheme is incorporated into the scoring auction under an environment of multidimensional bid competition.

2.2. Keyword Auctions

From the perspective of payment forms, the literature on keyword auctions includes pay-per-exposure (pay-per-impression) auctions and performance-based (pay-per-action) auctions (Zhu and Wilbur 2011). In pay-per-exposure, advertisers bid for impressions and pay each time their ad is displayed on a Web page (e.g., Chen et al. 2009, Edelman et al. 2007, Fukuda et al. 2013, Shin 2015). In a performance-based auction, advertisers bid and pay for measurable actions (click, call, sale, etc.) from customers (e.g., Agarwal and Mukhopadhyay 2016, Chen et al. 2010a, Liu and Chen 2006). Chen et al. (2010a) explored the design of performance-based unit-price contract auctions, in which bidders bid their unit prices and the winner is chosen based on both their bids and performance levels by a linear scoring rule. In addition, bidders with a low performance level can improve their performance at a certain cost. They found that the possible upgrade in bidders' performance level provides the auctioneer an incentive to modify the auction rules over time. Liu et al. (2010) proposed a keyword auction model in which advertisers bid their willingness-to-pay per click on their advertisements, and the advertising provider can require different minimum bids based on advertisers' click-generating potential. They showed that the revenue-maximizing minimum-bid policy with a linear scoring rule can generate higher revenue than standard pay-per-exposure auctions. Unlike the above works on performance-based keyword auctions, our model considers the multiple attributes of bids (quality and price) along with bidders' efforts under ex post satisfaction concern, and optimal scoring rule, including the reserve score, is derived.

2.3. Procurement Auctions and Procurement Risks in Supply Chain

The supply chain literature includes many papers on procurement auctions. Tunca and Zenios (2006) compared the use of auctions and long-term relational contracts given non-verifiable quality. Chen (2007) studied procurement contract auctions with a buyer-announced quantity-payment schedule. Wan and Beil (2009) explored the trade-offs between different levels of pre- and post-qualification when the manufacturer uses a request-for-quotes (RFQ) reverse auction to select the qualified supplier. Chaturvedi and Martinez-de-Albeniz (2011) considered a multi-sourcing problem with two-dimensional private information on exogenous production cost and supply reliability. Li and Scheller-wolf (2011) determined whether a buyer should specify order quantity before or after demand realization in procurement auctions. Li et al. (2015) investigated the design of procurement mechanism when the manufacturer has two-dimensional private information and the retailer makes the assortment planning. Gupta et al. (2015b) analyzed the descending mechanism design under the constraints of individual/group capacities and business rules separately. The uniqueness of our study is that the ex post performance, which is endogenously affected by promised quality and unobservable effort of supplier, is embedded into the ex-ante multi-attribute scoring auction.

This study focuses on the interaction of promised quality and effort, and on how bidder behaviors and auction design are influenced by the dynamics of uncertainty in different scenarios. Supply/procurement risks have been widely studied, including (1) quantity risk, such as random yield (e.g., Federgruen and Yang 2009, Gerchak and Parlar 1990) or random capacity (e.g., Ciarallo et al. 1994), and (2) quality risk, such as quality defects (e.g., Baiman et al. 2000 and Lim 2001) and non-verifiable quality risk/failure risk (e.g., Tunca and Zenios 2006). In our model, the procurement satisfaction risk differs, as it is endogenous and relates to bidder behaviors, that is, both promised quality and effort. Thus, we further scrutinize the impact of this risk on behaviors, utilities and mechanism designs, given the additive relationship between randomness and behaviors, which is commonly examined in the supply chain literature (e.g., Agrawal and Sechadri 2000, Chen 2005, Chu and Lai 2013).

In summary, we combine a multidimensional auction with a PBC to study procurement with *ex ante* bidding processes and ex-post satisfaction. This setting is common in service procurements but has not yet been investigated in the literature. We contribute to the literature on procurement auctions by investigating multi-attribute auctions in which uncertain satisfaction is determined by promised quality and unobservable effort, and by exploring crucial operational implications of both bidder behaviors and mechanism designs under various uncertainty environments. To the best of our knowledge, this is the first attempt to understand the mechanism design of a multi-attribute scoring auction with endogenous supply risk. We further analyze the impacts of additive uncertainty on bidding behaviors and auction design.

3. Base Model

3.1. Model Description

The basic setting of our model can be described as follows. The procurement auction consists of one buyer (i.e., government agency or corporation) and n bidders (suppliers).[1] The buyer who requests the service or product starts the auction process. At the beginning of the auction, the buyer announces its specific requests, the scoring rule describing its preference, and contingent payment depending on *ex-post* satisfaction. Bidders then submit their bids, which include both price and promised quality. After the buyer selects the winning bidder based on the announced scoring rule, the bidder then exerts effort to execute the project. On completion of the project, a contingent payment (i.e., either bonus or penalty) will be delivered from one party to the other based on the realization of uncertain satisfaction.

Specifically, the utility for the buyer comes from two sources: utility from promised quality $V(q)$ and utility from uncertain satisfaction $\lambda(\Delta q)$. Promised quality q in bid denotes the contractible standard and/or service level (e.g., project quality, delivery date, and engine service hours after maintenance), but the realization of quality $\tilde{q}$ is stochastic. Here, Δq denotes the difference between the promised quality q in bid and its realized performance $\tilde{q}$, that is, $\Delta q = \tilde{q} - q.V(q)$ is the benchmark of buyer utility in the uncertain procurement project, and $\lambda(\Delta q)$ formalizes the common notion of *ex post* buyer satisfaction, which is difficult to bid *ex ante* but verifiable *ex post*. Contingent transfers based on the *ex post* assessment of uncertain satisfaction are written into the contract, where the uncertain satisfaction can be observed by both parties and examined by a third party (e.g., an independent inspector) after project completion.

Bidders compete for the contract by bidding (q, b), where q and b denote the promised quality and bid price, respectively. Bidder i's cost function $c(q, \theta_i)$ increases in both q and type θ_i (i.e., private information of the bidder), which, to the buyer, is independent and identically distributed over $[\underline{\theta}, \bar{\theta}]$, with distribution F and density f. The monotonic cost function in q is reasonable, as a higher promised quality requires a higher investment. The winning bidder then invests unobservable effort e during the project. Note that the realized quality $\tilde{q}(q, e, \varepsilon)$ depends on q and e, as well as a stochastic component ε, which includes many other factors (i.e., weather, environmental uncertainty, etc.) that are uncontrollable by the supplier. $\lambda(\Delta q)$ takes a monetary value corresponding to the utility or disutility from the realized outcome, and $\lambda(\Delta q) \geq 0 (\lambda(\Delta q) < 0)$ if $\Delta q \geq 0 (\Delta q < 0)$. The expectation of $\lambda(\Delta q)$ is denoted by $\Lambda(q, e) = E[\lambda(\Delta q)]$. The buyer pays a performance bonus to the supplier if $\lambda(\Delta q) > 0$ and claims a performance penalty if $\lambda(\Delta q) < 0$. The amount of the *ex post* bonus/penalty $\alpha\lambda(\alpha \in [0, 1])$ is a linear function of the realization of satisfaction. The parameter α represents the allocation of the utility (disutility) from uncertain satisfaction between the buyer and supplier, and is determined by mechanism design. The uncertain satisfaction $\lambda(\Delta q) \in [\underline{\lambda}, \bar{\lambda}]$ follows a distribution function $H(\lambda|q, e)$, which is influenced by both promised quality and effort, where $H(\cdot|\cdot)$ is twice differentiable. The expected utility of the winning supplier θ_i, considering the disutility of effort $g(e)$, is given by

$$U_s(b, q, e|\theta_i) = b - c(q, \theta_i) + \alpha \cdot \Lambda(q, e) - g(e),$$

where $\alpha \cdot \Lambda(q, e) - g(e)$ is the expected utility from the uncertain satisfaction of contingent scheme, which can be either positive or negative. The expected utility of the buyer is given by

$$U_b = v(q) - b + (1 - \alpha) \cdot \Lambda(q, e),$$

where $V(q)$ is the buyer utility from promised quality q, and $(1 - \alpha) \cdot \Lambda(q, e)$ is the expected utility from *ex post* satisfaction/dissatisfaction. The expected social surplus (i.e., the sum of both supplier and buyer utility) is given by

$$W(q, e) = V(q) - c(q, \theta_i) + \Lambda(q, e) - g(e).$$

The contract is awarded according to a scoring rule known to all parties at the start of bidding. Following Asker and Cantillon (2008), we use a quasi-linear function $S(q, b) = s(q) - b$ to score bid (q, b), and the bidder with the highest score wins the procurement contract. Note that $s(q)$ is determined by the mechanism design. To ensure that our model is well-behaved, we make technical assumptions following the conventional literature.

Assumption 1. *The bidder's cost function $c(q, \theta)$ satisfies $c_{qq} \geq 0$, $c_{q\theta} > 0$ and $c_{qq\theta} \geq 0$, while the buyer utility from promised quality $V(q)$ satisfies $V_q > 0$ and $V_{qq} < 0$.*

The properties in Assumption 1 are commonly adopted in multi-attribute procurement auctions (e.g., Che 1993). For the supplier, the marginal quality cost increases in both q (weakly) and type θ. For the buyer, the utility from promised quality increases in q while the marginal utility decreases. These assumptions can be easily satisfied. For example, $c(q, \theta) = \theta q$ and $V(q) = q^{\frac{2}{3}}$.

Assumption 2. *The effort cost increases in e at an increasing rate, that is, $g_e > 0$, $g_{ee} \geq 0$.*

The convex property of effort cost function in Assumption 2 is also widely adopted in the literature (e.g., Rees 1985), which reflects that the marginal disutility of the supplier from exerting more effort increases. A common example of the effort cost is $g(e) = \frac{1}{2}e^2$.

Assumption 3. *The realized quality $\tilde{q}$ increases in q, e and ε, and further $\tilde{q}_{qq} \leq 0$ and $\tilde{q}_{ee} \leq 0$. The satisfaction $\lambda(\Delta q)$ increases in Δq at a decreasing rate, that is, $\lambda' \geq 0$, $\lambda'' \leq 0$.*

Assumption 3 indicates that both higher promised quality in bid and higher effort during the project can lead to higher realized quality performance stochastically, while at the same time, higher promised quality decreases the probability of achieving an exceeding *ex post* outcome (i.e., Δq). That is, the increase of promised quality q has two simultaneous effects in our model: to enhance satisfaction (i.e., increase $\tilde{q}$)[2] and to raise reference (i.e., increase the difficulty to reach a higher Δq). We define the first effect as the enhancement role and the second as the reference role in the remainder of our study. If $\Delta q_q \leq 0$, it indicates that the reference role dominates the enhancement role; if $\Delta q_q > 0$, it means that the enhancement role dominates the reference role. From $\lambda' \geq 0$, one can easily infer that $\Lambda_q(q, e) \leq 0$ if $\Delta q_q \leq 0$, which implies that the expected satisfaction decreases in promised quality, while $\Lambda_q(q, e) > 0$, if $\Delta q_q > 0$, which indicates that the expected satisfaction increases in promised quality. In particular, we can apply the additive relationship between promised quality, effort and randomness, $\tilde{q}(q,e,\varepsilon) = re + kq + \varepsilon (r \geq 0, k \geq 0)$ and $\Delta q = re - (1-k)q + \varepsilon$, with linear satisfaction $\lambda(\Delta q) = \mu \cdot \Delta q (\mu > 0)$ or nonlinear satisfaction $\lambda(\Delta q) = \mu \cdot (1 - exp(-\Delta q))$. Under these specifications, it can easily verified that the requirements of Assumption 3 are satisfied.

Assumption 4. *$H(\lambda|q,e)$ satisfies the convexity distribution function condition, that is, $H_e(\lambda|q,e) \leq 0$, $H_{ee}(\lambda|q,e) \geq 0$ for $\forall q$, and $H_{qq}(\lambda|q,e) \geq 0$ for $\forall e$.*

This assumption is a regularity condition and is commonly adopted in the moral-hazard literature, which ensures that the supplier's problem is unimodal and thus enables the first-order approach (see Grossman and Hart 1983, Holmstrom 1979, Jewitt et al. 2008). Many common distributions of random shock can lead to this condition, for instance, the uniform distribution and the gaussian distribution.

3.2. Promised Quality and Unobservable Effort

Hereafter, the supplier's subscript i is dropped from θ_i for notational convenience. We focus on the scenario where the buyer uses the first-score auction so that the bidder with highest score wins, and define the term $max_{q,e}\{s(q(\theta)) - c(q(\theta),\theta) + \alpha \cdot \Lambda(q(\theta), e(\theta)) - g(e(\theta))\}$ as "pseudo-type," which is analogous to the "value" in regular selling auctions.

Lemma 1. *Promised quality $q^*(\theta)$ and exerted effort $e^*(\theta)$ maximize the pseudo-type, that is, $\{q^*(\theta), e^*(\theta)\} = argmax\{s(q(\theta)) - c(q(\theta),\theta) + \alpha \cdot \Lambda(q(\theta), e(\theta)) - g(e(\theta))\}$ for all $\theta \in [\underline{\theta}, \bar{\theta}]$.*

Lemma 1 shows that bidders must jointly optimize promised quality and effort before submitting a bid price. This essential characteristic of bidder behavior differentiates our study from the existing literature. That is, the bidder's strategy not only considers the winning probability, the deterministic cost in terms of promised quality (e.g., Asker and Cantillon 2008 and Che 1993), and the expected cost in terms of penalty bid and risk type (exogenous failure probability) (e.g., Chaturvedi and Martinez-de-Albeniz 2011 and Chen et al. 2010b), but also the expected utility from uncertain satisfaction, which is affected by both promised quality and endogenous effort. Thus, the pseudo-type in our model has two distinct features: (1) *ex ante* (before bidding) and interim (after bidding but before the completion of the project) uncertainty and (2) moral hazard. As a result, Lemma 1 extends previous studies of the existence of generalized value (i.e., pseudo-type) to a richer context that incorporates the endogenous service risk.

Note that the sign of Λ_{qe} depicts the relationship between effort and promised quality in terms of marginal contribution to the expected uncertain satisfaction. The relationship is defined as *complementary* if $\Lambda_{qe} > 0$ and *substitutable* if $\Lambda_{qe} < 0$. Essentially, the buyer's satisfaction utility function can be considered as either quality sensitive (complementary) or effort sensitive (substitutable). If increasing promised quality increases the marginal contribution of effort to the buyer's satisfaction, then the buyer's satisfaction type is quality sensitive. We refer to such buyers as quality sensitive type, since they prefer an initial higher promised quality at the auction. In contrast, the substitutable type can be regarded as effort sensitive (or non-quality sensitive), because a lower initial promised quality generates a higher marginal contribution from the effort to satisfaction. In practice, the quality sensitive type represents the buyer whose satisfaction is higher depending on high promised quality, while the effort sensitive type represents the buyer who prefers high effort and its consequence (a high Δq) over high promised quality alone. For example, consider the nonlinear satisfaction function $\lambda(\Delta q) = \mu \cdot (1 - exp(-\Delta q))$, where $\mu > 0$, $\Delta q = re - (1-k)q + \varepsilon (r \geq 0, k \geq 0)$, and $\varepsilon \sim U[a, b]$. It can be verified that $\Lambda_{qe} > 0$ if $k < 1$, which means that the promised quality and effort complement with each other to improve the satisfaction. Meanwhile, if $k > 1$, $\Lambda_{qe} < 0$ which indicates that promised quality and effort substitute with each other to improve the satisfaction.

We summarize the impact of second-order condition Λ_{qe} on optimal promised quality and effort levels as follows.

Proposition 1. *$q^*(\theta)$ always decreases in θ.*

- *When $\Lambda_{qe} > 0$ (i.e., quality sensitive), we find that $e^*(\theta)$ decreases in θ.*
- *When $\Lambda_{qe} < 0$ (i.e., effort sensitive), we find that $e^*(\theta)$ increases in θ.*

All proofs are provided in Appendix S1. Let us consider the case where supplier production cost decreases, that is, a smaller θ. In this case, the supplier should either improve cost-related quality or lower product (service) price accordingly, which could be considered as the prime effect of cost reduction. However, whether the supplier should exert more or less effort when satisfaction is uncertain remains unclear. Proposition 1 provides an answer to this question. When production cost of the supplier decreases, the firm should exert less effort if the buyer is effort sensitive, since the increased promised quality lowers the marginal efficiency of effort regarding its contribution to satisfaction. If the buyer is the quality sensitive type, then greater effort from the supplier should be exerted, because a higher promised quality increases the marginal efficiency of effort on satisfaction.

PROPOSITION 2. *The promised quality under the scenario of dominant reference role (i.e., $\Delta q_q \leq 0$) is lower than that under the scenario of dominant enhancement role (i.e., $\Delta q_q > 0$).*

The intuition of this result is as follows. Under the satisfaction concern, the supplier needs to balance the utility of the initial promised quality and performance contingency payment. As a result, we find that it is optimal for the supplier to bid less aggressively on the initial promised quality when the promised quality decreases the expected satisfaction than when the promised quality increases it. Such actions also positively influence buyers' belief of a higher probability of *ex post* satisfaction.

3.3. Bid Price and Information Rent

Next, we analyze the bidding strategy of price.

LEMMA 2. *The unique optimal bid price of the bidder with θ is $b^*(\theta) = c(q^*(\theta), \theta) - \alpha \cdot \Lambda(q^*(\theta), e^*(\theta)) + g(e^*(\theta)) + \int_{\theta}^{\bar{\theta}} c_\theta(q^*(t), t) \cdot \left(\frac{1-F(t)}{1-F(\theta)}\right)^{n-1} dt$.*

There are several immediate observations from Lemma 2. To begin with, if effort does not affect satisfaction, the total expected cost can be simplified to $c(q^*(\theta)) - \alpha \cdot \Lambda(q^*(\theta))$, where price only relates to promised quality. Second, two endogenous determinants (i.e., promised quality and effort) govern the cost part of the bid in our model. In the model of Chen et al. (2010b), where auctions incorporate risk, the cost comprises an exogenous cost and an exogenous "probability of successful completion" multiplied by the one-dimensional endogenous penalty. As for the information rent, in our model, $\int_{\theta}^{\bar{\theta}} c_\theta(q^*(t), t) \cdot \left(\frac{1-F(t)}{1-F(\theta)}\right)^{n-1} dt$, it is affected by both the winning probability and quality cost, whereas in the model of Chen et al. (2010b) it is only affected by the winning probability.

COROLLARY 1. *Bidders obtain less information rent when the reference role is dominant (i.e., $\Delta q_q \leq 0$) than when the enhancement role is dominant (i.e., $\Delta q_q > 0$).*

Corollary 1 shows that compared with the case where promised quality can increase the expected satisfaction (i.e., $\Lambda_q(q, e) > 0$), bidders receive less information rent when promised quality decreases the expected satisfaction (i.e., $\Lambda_q(q, e) \leq 0$). That is, the bidders obtain less information rent when the reference role of promised quality dominates the enhancement role. The intuition of this result is because that the bidders will submit a lower promised quality when reference role dominates (Proposition 2). An interesting implication of Proposition 2 and Corollary 1 is that the uncertain satisfaction that accompanies contingent payments can either decrease or increase the supplier's surplus, depending on the interplay between the two roles of promised quality. In the next section 5, we investigate the impact of uncertain satisfaction on buyer utility and social surplus.

4. Mechanism Design

In this section, we focus on the mechanism design facing the buyer. We consider two mechanisms: (1) "Efficient Mechanism" and (2) "Optimal Mechanism." "Efficient Mechanism" is the efficient allocation design of the scoring rule and contingent transfer that maximizes expected social surplus, while "Optimal Mechanism" represents the construction of a scoring rule and contingent transfer that maximizes expected buyer utility.

4.1. Efficient and Optimal Mechanism

PROPOSITION 3. *Efficient mechanism requires $\alpha = 1$ and $s(q) = V(q)$.*

Proposition 3 shows that if the buyer wishes to maximize expected social surplus, she should apply her true preference to evaluate the promised quality, and require the supplier to fully shoulder the risk of satisfaction uncertainty. The intuition of this result is that promised quality and effort must both be efficient in an efficient mechanism. The winner assumes all moral hazard with no effort distortion, and therefore she must carry the risk by sharing the uncertainty fully with $\alpha = 1$. To derive the optimal mechanism, we first present the expected utility of the buyer, where $\theta_{(1)}$ is the first-order statistic, that is $\theta_{(1)} = min_i\{\theta_i\}$.

LEMMA 3. *Expected buyer utility prior to bidding is* $E(U_b) = E_{\theta_{(1)}}\{W(q(\theta_{(1)}), e(\theta_{(1)})) - c_\theta(q(\theta_{(1)}), \theta_{(1)})F(\theta_{(1)})/f(\theta_{(1)})\}$ *where* $\theta_{(1)} = min_i\{\theta_i\}$, $i = 1, 2, \ldots, n$; $c_\theta(q, \theta)$ *is the partial derivative w.r.t.* θ, *and* $W(q(\theta), e(\theta)) = V(q(\theta)) - c(q(\theta), \theta) + \Lambda(q(\theta), e(\theta)) - g(e(\theta))$ *is the social surplus generated by the supplier of type* θ.

Note that the expected buyer utility can be characterized by two equivalent expressions: the direct form, and taking the difference between social surplus and information rent. Here we adopt the latter because of expositional convenience. In mechanism design theory, buyer utility is similar to the notion of "*virtual valuation.*" However, *virtual valuation* in our model involves both multidimensional bids and moral hazard. This generates a double uncertainty for the buyer.

PROPOSITION 4. *Under the optimal mechanism,* $\alpha = 1$ *and* $s(q) = V(q) - D(q)$, *where* $D(q) = \int_l^q [F(q_0^{-1}(s))/f(q_0^{-1}(s))] \cdot c_{q\theta}(s, q_0^{-1}(s))ds$ *for* $q \in [q_0(\bar{\theta}), q_0(\underline{\theta})]$, *and* $(q_0(\theta), e_0(\theta))$ *is the solution that maximizes* $\{W(q(\theta), e(\theta)) - c_\theta(q(\theta), \theta)F(\theta)/f(\theta)\}$.

The managerial implication of Proposition 4 is that the buyer should not expect to gain further from contingent transfers.[3] Note that the information rent is directly related to the promised quality in bid. Under the optimal mechanism, the distorted scoring function $V(q) - D(q)$ maximizes buyer utility and decreases both rent and promised quality. Thus, $V(q) - D(q)$ constructs the *virtual valuation*. In this case, the effort undertakes the role of a risk hedging without a further distortion. The effort can be considered as "relatively efficient" in terms of any distortion of promised quality. Therefore, as the moral hazard is undistorted, the winning bidder assumes the full risk share assigned by the optimal auction. The question of how satisfaction uncertainty affects buyer utility under the optimal mechanism is particularly interesting. Compared with the case when the enhancement role dominates the reference role, on the one hand, Corollary 1 illustrates that the supplier's information rent gets squeezed when the reference role dominates the enhancement role, which benefits the buyer. On the other hand, Proposition 2 states that the bidder will bid lower in the quality dimension with dominant reference role, which hurts the buyer. As a result, whether the buyer utility improved or not depends on the magnitude between the two factors stated above. We further discuss the impact of uncertainty on buyer utility and bidder's behaviors in section 5.

Hitherto, we have adopted the common assumption (e.g. Che 1993) that $V(q)$ is sufficiently large even with relatively small promised quality q, which suggests that the worst type $\bar{\theta}$ still deserves consideration from the buyer. Clearly, this assumption is too restrictive in many practical examples. Next, we consider the scenario in which this previous assumption is relaxed; that is, the buyer may get negative utility from certain suppliers. As a result, we need to impose a zero reservation constraint for the buyer. That is, the optimal mechanism requires a non-negative constraint for buyer utility $U_b(q_0(\theta), e_0(\theta))$, $U_b(q_0(\theta), e_0(\theta)) = W(q_0(\theta), e_0(\theta)) - c_\theta(q_0(\theta), \theta)F(\theta)/f(\theta) \geq 0$, where $\{q_0(\theta), e_0(\theta)\} = argmax\{W(q(\theta), e(\theta)) - c_\theta(q(\theta), \theta)F(\theta)/f(\theta)\}$.

Based on the common requirement of regularity in mechanism design, we further assume that $c_\theta(q(\theta), \theta) \cdot F(\theta)/f(\theta)$ increases in θ. Following the envelope theorem, we can show that $dU_b(q_0(\theta), e_0(\theta), \theta)/d\theta < 0$. With this monotonicity property and Proposition 4, the following strategy on reserve score becomes optimal.

PROPOSITION 5. *An optimal reserve score* $\tilde{S}$ *exists and is given by* $\tilde{S} = V(q_0(\tilde{\theta}) - D(q_0(\tilde{\theta})) - c(q_0(\tilde{\theta}), \tilde{\theta}) + \Lambda(q_0(\tilde{\theta}), e_0(\tilde{\theta})) - g(e_0(\tilde{\theta}))$ *for the buyer, where* $\tilde{\theta} = \bar{\theta}$ *if* $U_b(q_0(\theta), e_0(\theta)) \geq 0$ *for all* θ, $\tilde{\theta} = \underline{\theta}$ *if* $U_b(q_0(\theta), e_0(\theta)) < 0$ *for all* θ, *and* $\tilde{\theta}$ *is the largest solution to* $U_b(q_0(\tilde{\theta}), e_0(\tilde{\theta})) = 0$ *otherwise. With* $\tilde{S}$, *the corresponding price bidding strategy for all* $\theta \leq \tilde{\theta}$ *is* $b_s(\theta) = c(q_0(\theta), \theta) - \Lambda(q_0(\theta), e_0(\theta)) + g(e_0(\theta)) + \int_\theta^{\tilde{\theta}} c_\theta(q_0(t), t) \cdot \left(\frac{1-F(t)}{1-F(\theta)}\right)^{n-1} dt$.

Regulated by $\tilde{S}$, the bidder with the highest score is selected if the score exceeds $\tilde{S}$. Otherwise, no bidder will be selected. The reserve score $\tilde{S}$ is the minimum acceptable score to ensure the non-negative utility for the buyer, which is analogous to the idea of reserve price in a selling auction. We find that the bidder asks for less information rent when there is a reserve score, and Lemma 1 still holds. Any supplier with type $\theta \leq \tilde{\theta}$ will bid $(q_0(\theta), b_s(\theta))$ to ensure that $S(q_0(\theta), b_s(\theta)) \geq \tilde{S}$. In contrast, suppliers of types $\theta > \tilde{\theta}$ do not participate in the auction, because their bid price $s(q_0(\theta)) - \tilde{S}$ will lead to a negative expected utility. Thus, by applying the reserve score $\tilde{S}$ to exclude high-cost suppliers (i.e., $\theta > \tilde{\theta}$), the buyer can reduce the information rent for types $\theta \leq \tilde{\theta}$ and guarantee a non-negative reservation utility based on the requirement of optimal mechanism design.

The most important managerial implication from Proposition 5 is that neither reserve quality nor reserve price alone is sufficient to achieve the optimal mechanism. Specifically, if the buyer only sets a reserve quality $q_0(\tilde{\theta})$, then the behaviors of suppliers with types of $\theta \leq \tilde{\theta}$ are unaffected. Suppose that bidders of type $\theta > \tilde{\theta}$ participate. Their promised qualities in bid must be $q_0(\tilde{\theta})$, and they can increase their bid prices to achieve non-negative utility. In this case the buyer cannot exclude high-cost suppliers (i.e., $\theta > \tilde{\theta}$. If the buyer only sets a reserve price, all types of suppliers can participate. The intuition of this result is as follows. Any type of bidder, without violating the reserve price, can make a bid with sufficiently low promised quality to achieve a positive utility. The implication of this unique reserve score can be explained in two ways. First, a single-dimensional reserve (price or quality) in a multidimensional auction is insufficient; as a result, the buyer must impose a minimum requirement on both promised quality and bid price to exclude undesired types from the pool of potential suppliers. Second, the reserve score in a single-stage procurement auction works similarly to the pre-qualification process in multi-stage auctions, and ensures that only qualified bidders can participate in the subsequent bidding. To the best of our knowledge, this finding has not been emphasized in the previous procurement auction literature.

Recent developments in information technology have facilitated the implementation of multi-attribution auction. Buyers submit their needs through an electronic platform and solicit bids from the pre-qualified suppliers. When the buyer submits the specifications of the procurement, she also reports her valuation and/or scoring rules on the request items, which includes both price and non-price dimensions. To respond, the suppliers submit their bids, which include their promised quality and price. Further, we observe that many buyers in practice also set the minimum acceptable quality level and ceiling price together, which can be translated to a reserve score in our setting. Our results here provide practical guidance regarding how to design and implement procurement auctions when satisfaction concern is significant.

COROLLARY 2. *The quality distortion $D(q)$ of optimal mechanism under the scenario of dominant reference role in promised quality (i.e., $\Delta q_q \leq 0$), is less than that under the scenario of dominant enhancement role (i.e., $\Delta q_q > 0$).*

Corollary 2 provides an immediate insight for procurement managers. When promised quality involves an uncertain performance with a dominant reference role, bidders will submit lower bids because a high-promised quality decreases the possibility of fulfilling or exceeding the buyer's expectations upon completion of the project. Accordingly, the buyer deploys an optimal scoring rule with mild distortion. For the reverse case with a dominant enhancement role, the buyer should distort the promised quality more aggressively.

4.2. Bidder Behaviors under Efficient and Optimal Mechanism

We denote $\hat{q}$ and $\hat{e}$ as promised quality and effort in *efficient mechanism*, respectively, and q^* and e^* as those in *optimal mechanism*. Comparing the bidder's behaviors in efficient and optimal mechanisms, we obtain the following proposition.

PROPOSITION 6. *When the buyer is quality sensitive (i.e., $\Lambda_{qe} > 0$), both promised quality and effort are lower under optimal mechanism than under efficient mechanism (i.e., $\hat{q} > q^*$ and $\hat{e} > e^*$); when the buyer is effort sensitive (i.e., $\Lambda_{qe} < 0$), promised quality is lower under optimal mechanism than under efficient mechanism (i.e., $\hat{q} > q^*$), while the effort is higher under optimal mechanism than under efficient mechanism (i.e., $\hat{e} < e^*$).*

Proposition 6 illustrates that promised quality is distorted downwardly as expected. However, whether the effort is distorted downwardly or upwardly depends upon the relationship between promised quality and effort. The optimal mechanism adversely affects the interest (utility) of suppliers compared with the efficient mechanism. Effort thus acts as a loss hedging tool in the scenarios of both quality sensitivity ($\Lambda_{qe} > 0$) and effort sensitivity ($\Lambda_{qe} < 0$). When $\Lambda_{qe} > 0$, the optimal effort under optimal mechanism is lower than that under the efficient mechanism (i.e., $e^* < \hat{e}$). The intuition of this result is that for a quality sensitive buyer, the lower promised quality will reduce the increasing rate of expected satisfaction in effort, which consequently decreases the supplier's incentive to exert more effort. When $\Lambda_{qe} < 0$, the optimal effort under optimal mechanism becomes higher than that under the efficient mechanism (i.e., $e^* > \hat{e}$). The intuition here is because for an effort-sensitive buyer, there is an upward distortion of the supplier's effort due to the greater marginal increase of buyer satisfaction from effort and associated reward for the supplier to exceed the promised quality level.

5. Impact of the Uncertainty

The above discussion illustrates that uncertainty regarding satisfaction will affect promised quality, effort and optimal mechanism design. A more thorough assessment of the impact of ε requires specific functional form of Δq and $\lambda(\Delta q)$. First, we define $re - (1 - k)q(r \geq 0,\ k \geq 0)$ as the *behavior factor*, which is the deterministic component of Δq and contains two decisions of the bidder. r denotes effectiveness of effort, and k is a coefficient that represents the difference between the reference and enhancement roles that results from promised quality q. When $k < 1$

($k > 1$), the reference role dominates (is dominated by) the enhancement role. When $k = 1$, the enhancement role fully offsets the reference role.

Assume $\varepsilon \sim U[a, b]$ with $0 < a \leq b$. The stochastic factor ε applies to Δq additively. That is, $\Delta q(e, q, \varepsilon) = re - (1 - k)q + \varepsilon$, and we label it as "additive uncertainty," which appears widely in the supply chain literature (e.g., Agrawal and Sechadri 2000, Chen 2005, Chu and Lai 2013). In this section, we consider both linear and the more general nonlinear satisfaction functions and examine two types of uncertainties.[4] First, we consider $b = a + \tau(\tau \geq 0)$, and investigate how the increase of τ influences the decisions of the buyer and the bidders. Note that in this case, both the mean and the variance of uncertainty ε will increase. Second, we consider $a = c - \sigma$ and $b = c + \sigma(0 \leq \sigma < c)$, which allows us to explore the impact of variability σ alone while keeping the mean of ε fixed.

5.1. Impact of Uncertainty on Promised Quality and Effort

We first analyze the impacts of τ and σ on the optimal promised quality and effort of the suppliers.

Proposition 7. *Under linear $\lambda(\Delta q)$, q^* and e^* are independent of τ and σ. Under nonlinear $\lambda(\Delta q)$, (i) e^* always decreases in τ, and q^* increases (decreases) in τ if $k < 1(k > 1)$; (ii) e^* increases (decreases) in σ if $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma > (<)0$, and q^* increases (decreases) in σ if $(1 - k) \cdot \partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma < (>)0$.*

The additive uncertainty and linearity of $\lambda(\Delta q)$ ensure that the marginal contributions of promised quality q and effort e on the expected satisfaction are independent of τ and σ. Meanwhile, the marginal effects of τ and σ on satisfaction are also independent of q and e. These facts consequently lead to the result that q^* and e^* are independent of τ and σ.

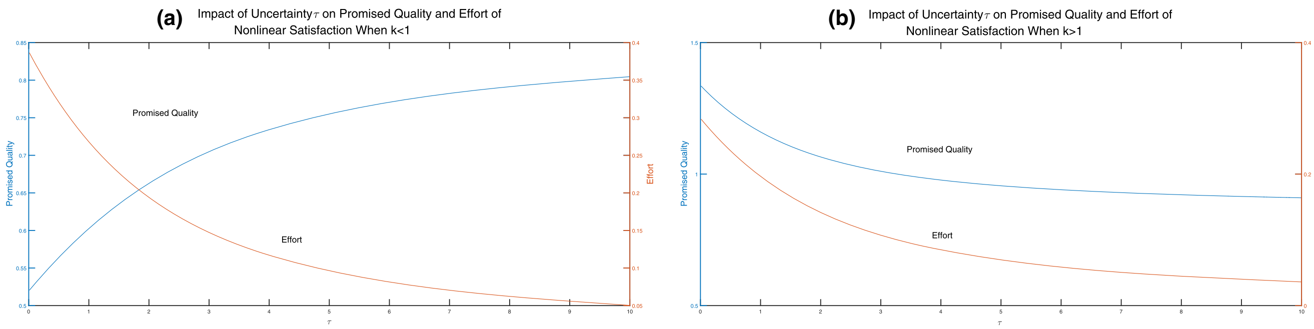
For nonlinear $\lambda(\Delta q)$, the expectation of $\lambda(\Delta q)$ increases in τ for given q and e. Note that an increase of τ leads to a greater mean of the random component along with larger variance, which generates a higher Δq. One might intuitively guess that the bidder might further take advantage of this positive effect from uncertainty by increasing e and decreasing q when reference role is dominant (i.e., $k < 1$), or increasing both e and q when enhancement role is dominant (i.e., $k > 1$). However, this is not the case here. Rather, the bidder actually decreases e and increases q when the reference role is dominant, and decreases both e and q when the enhancement role is dominant. The intuition of this result is that the concavity of $\lambda(\Delta q)$ allows the bidder to exploit a "free ride" on this advantage. Figure 1a and b illustrate the impact of τ on the promised quality and effort with dominant reference role ($k < 1$) and dominant enhancement role ($k > 1$), respectively. In all the figures, we apply $v(q) = q^{\frac{2}{3}}$, $c(\theta, q) = \theta \cdot q$, $\lambda(\Delta q) = \mu \cdot \Delta q$ (linear), $\lambda(\Delta q) = \mu \cdot (1 - \exp(-\Delta q))$ (nonlinear), $g(e) = e^2/2$, $r = 0.6$, $a = 1$, $c = 5$, $n = 10$, $\theta = 0.6$, $\mu = 2$ for nonlinear $\lambda(\Delta q)$, and the results are robust to the changes of parameters.

Unlike τ, the increase of σ leads to more variability of the random component but keeps the mean unchanged. For nonlinear $\lambda(\Delta q)$, when σ increases, the marginal contribution of effort e on the expectation of satisfaction may increase or decrease but will always be positive. Thus, we observe that the bidder increases her effort when $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma > 0$ due to the enhanced marginal contribution, while the bidder decreases her effort when $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma < 0$ due to the reduced marginal contribution. Recall that the marginal contribution of promised quality q on the expectation of $\lambda(\Delta q)$ could be either positive or negative, depending on the interplay between the reference role and enhancement role. Meanwhile, the impact of σ on the marginal contribution of promised quality q to satisfaction, that is, $\partial^2\Lambda(q, e, \sigma)/\partial q\partial\sigma$, has the opposite (same) direction with that of effort e when $k < 1$ ($k > 1$). Therefore, Proposition 7 illustrates that when $k < 1$, the marginal contribution of promised quality q on satisfaction is negative due to its dominant reference role, and the bidder increases (decreases) its promised quality when $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma < 0$ ($\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma > 0$) due to the weakened (strengthened) negative contribution. Similarly, when $k > 1$, the bidder increases (decreases) its promised quality when $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma > 0$ ($\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma < 0$) since the positive marginal contribution of promised quality increases (decreases) in σ. Figure 2a and b illustrate the impact of σ on the promised quality and effort with dominant reference role ($k < 1$) and dominant enhancement role ($k > 1$), respectively, with the nonlinear $\lambda(\Delta q) = \mu \cdot (1 - \exp(-\Delta q))$. It can be proved that with the negative exponential form of satisfaction, $\partial^2\Lambda(q, e, \sigma)/\partial e\partial\sigma > 0$ always holds. Therefore, e^* increases in σ in both Figure 2a and b, and q^* decreases in σ in Figure 2a and increases in σ in Figure 2b. Recall that the information rent of the bidder increases in promised quality (Lemma 2), and thus the impact of uncertainty (τ or σ) on information rent immediately follows.

Further, we also investigate the impact of effort cost on the promised quality and effort under nonlinear satisfaction, which is illustrated in Figure 3.

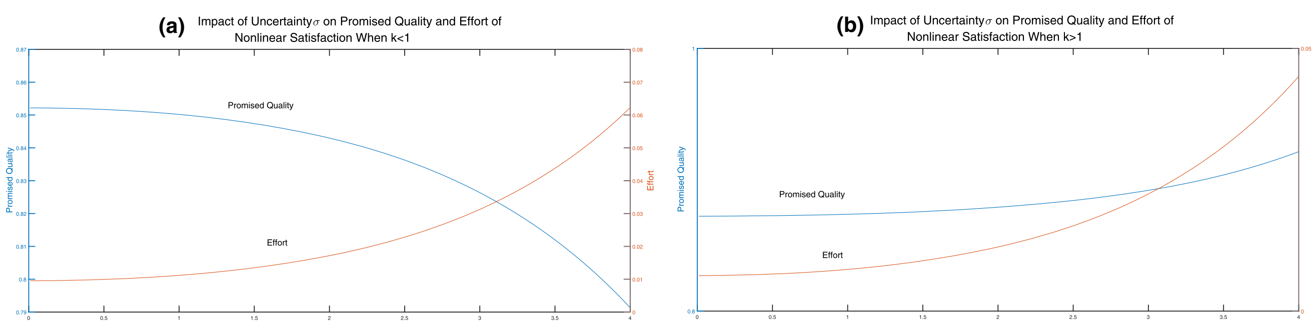
It is intuitive to see that when the marginal disutility of effort increases, the supplier will decrease the effort. However, the impact of effort cost on promised quality is not monotonic but depends on the whether

Figure 1 Impact of τ on Supplier's Behaviors [Color figure can be viewed at wileyonlinelibrary.com]



Note: k = 0.8 for Figures 1a, 2a, 3a, 4a and b; k = 1.2 for Figures 1b, 2b and 3b.

Figure 2 Impact of σ on Supplier's Behaviors [Color figure can be viewed at wileyonlinelibrary.com]



the satisfaction function is quality sensitive or effort sensitive. When promised quality and effort complement with each other ($k < 1$), we observe that the promised quality decreases due to the increased negative contribution of promised quality on satisfaction (which is generated by decreased effort) as shown in Figure 3a; when the promised quality and effort substitute with each other ($k > 1$), the promised quality increases since the positive contribution of promised quality on satisfaction increases as shown in Figure 3b.

5.2. Impact of Uncertainty on Buyer Utility and Optimal Mechanism Design

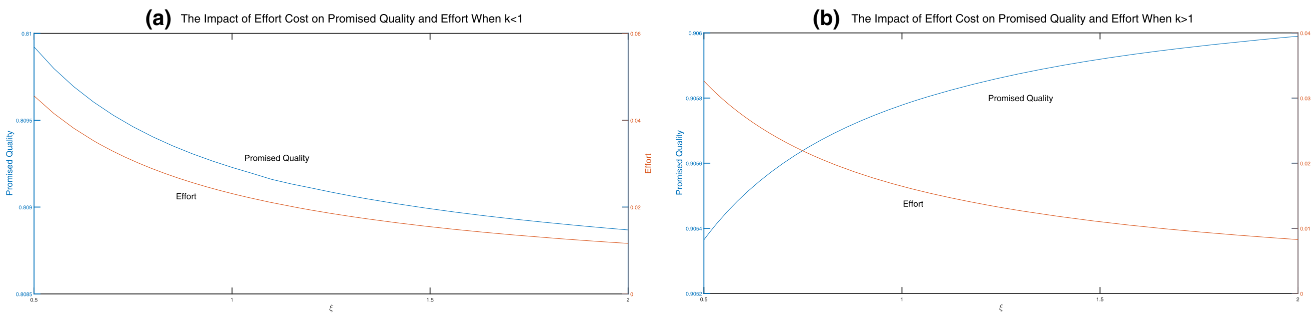
In this subsection, we focus on analyzing the impacts of τ and σ on buyer *ex ante* utility and the optimal mechanism design. The quality distortion $D(q)$, as the central point of the optimal mechanism, regulates q^* and e^* on the bidder's side; thus, setting the distortion appropriately is crucial in helping the buyer to maximize utility.

PROPOSITION 8. *Buyer's expected utility increases in τ, while it is independent of σ under linear $\lambda(\Delta q)$ and increases (decreases) in σ under nonlinear $\lambda(\Delta q)$ if $\partial\Lambda(q, e, \sigma)/\partial\sigma > 0(<0)$.*

Proposition 8 shows that the buyer's *ex ante* utility increases in τ under both linear and nonlinear $\lambda(\Delta q)$ due to the fact that the mean of Δq increases in τ, which is illustrated in Figure 4a. In particular, the buyer's expected utility increases in τ at constant rate given linear $\lambda(\Delta q)$, and increases at a decreasing rate given nonlinear $\lambda(\Delta q) = \mu \cdot (1 - exp(-\Delta q))$. Under linear $\lambda(\Delta q)$, the constant rate of buyer utility increase in τ implies that the increment of buyer utility is independent of q and e, and thus the degree of distortion is independent of τ. Under nonlinear $\lambda(\Delta q)$, note that the marginal positive effect of τ on buyer utility ($dU_b(q, e)/d\tau$) always decreases in e, and increases (decreases) in q if $k < 1$ ($k > 1$). Therefore, a higher (lower) q under $k < 1$ ($k > 1$) and lower e boost the rate of increase of buyer utility. Consequently, the optimal mechanism imposes a more significant (milder) distortion.

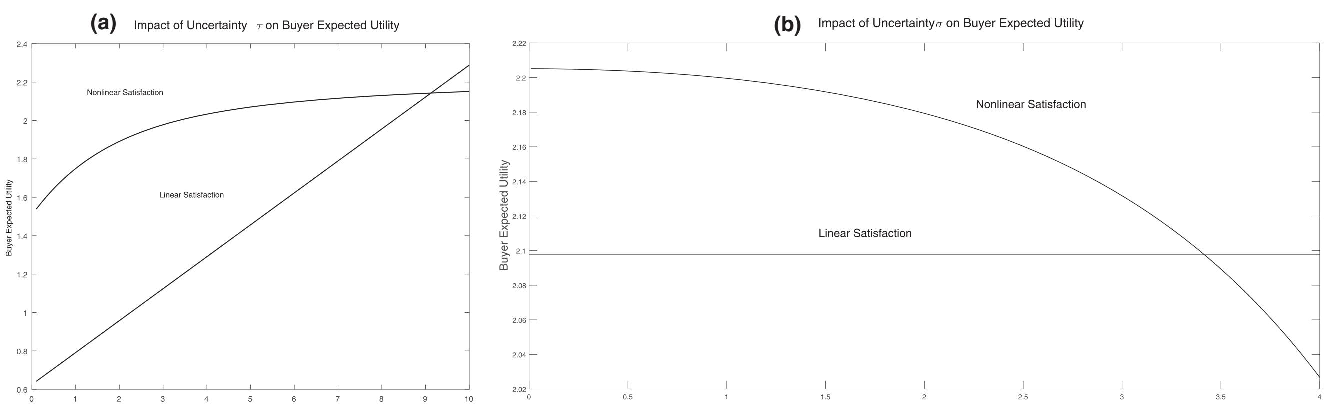
In contrast to τ, under linear $\lambda(\Delta q)$, the buyer's expected utility is independent of σ due to the constant mean of Δq, and thus the degree of distortion is also independent of σ. Interestingly, under nonlinear $\lambda(\Delta q)$, the impact of σ on buyer utility depends on its impact on satisfaction ($\partial\Lambda(q, e, \sigma)/\partial\sigma$). When satisfaction increases in σ, buyer benefits from the increase of uncertainty; the

Figure 3 Impact of Effort Cost on Supplier's Behaviors [Color figure can be viewed at wileyonlinelibrary.com]



Note: $g(e) = \xi e^2/2, \varepsilon \sim U[2, 6]$ in Figure 3.

Figure 4 Impact of Uncertainty on Buyer's Expected Utility



Note: $\theta \sim$ U[0.5, 1.5] in Figure 4.

opposite is true if satisfaction decreases in σ. Similar to τ, the impact of σ on quality distortion in an optimal mechanism relies on the impact of σ on promised quality. Therefore, the buyer adopts different levels of distortion on the promised quality to respond to different effects of uncertainty. Figure 4b illustrates the impacts of σ on buyer utility under linear and nonlinear satisfaction. In particular, with nonlinear $\lambda(\Delta q) = \mu \cdot (1 - \exp(-\Delta q))$, $\partial\Lambda(q, e, \sigma) / \partial\sigma < 0$ always holds, which implies that the buyer's expected utility decreases in σ.

In summary, we analyze the impacts of two uncertainty types on the bidder's and buyer's behaviors. Under linear satisfaction, promised quality and effort remain unchanged with uncertainty, while the buyer's expected utility increases in uncertainty when both mean and variance of the uncertainty increase, but remains unchanged when only the variance of uncertainty increases. Under nonlinear satisfaction, the uncertainty impact depends on the types of uncertainty, two roles of promised quality, and the marginal contributions of promised quality and effort on satisfaction. Conventional wisdom suggests that bidders and buyers will both be hurt by high uncertainty. However, our results reveal that a win-win situation (i.e., Pareto improvement) can be achieved along with two types of uncertainty increment. Further, to maximize the buyer's revenue, the bidder's behaviors are regulated by the adjusted mechanism where the core is the quality scoring rule. Larger (smaller) distortion always accompanies the increasing (decreasing) promised quality; such adjustments accommodate different bidder types due to the nature of the optimal scoring rule.

6. Extensions

In this section, we extend our base model in two directions. To begin with, we consider the scenario where the promised quality is deterministic and can be achieved with certainty. In the second extension, we relax the assumption that all bidders share the same cost of exerting the efforts by considering a scenario where the effort costs from different suppliers are different.

6.1 Deterministic Performance of Promised Quality

In the base model, we assume that the realized performance of the promised quality is stochastic. This is true in many practical scenarios. However, in some circumstances, the realization of promised quality can be achieved with certainty as well. To incorporate this realistic perspective into consideration, we consider an alternative model in which the promised quality in bid is deterministic while the *ex-post* satisfaction remains uncertain. This is because that the buyer's satisfaction is determined by not only the contractual element (e.g., promised quality) but also the non-contractual factor (e.g., unobservable effort). In other words, the outcome of buyer's satisfaction relies on both "hard" evidence and "soft" experiences/perceptions which are largely determined by the unobservable effort provided by the supplier.

For exposition, we only introduce the differences between the extended model and base model here. The degree of uncertain satisfaction $\lambda(q, e, \varepsilon)$ depends on q and e, as well as random variable ε. Contingent payment $\alpha\lambda(q, e, \varepsilon)$ is the bonus (penalty) of the supplier if $\lambda(q,e,\varepsilon) > 0$ ($\lambda(q,e,\varepsilon) < 0$). We denote the expectation of satisfaction as $\Phi(q,e) = E[\lambda(q,e,\varepsilon)]$. Similar to Assumption 3 for the base model, it has the following properties, $\Phi_e(q, e) \geq 0$, $\Phi_q(q, e) \geq 0$, $\Phi_{ee}(q, e) \leq 0$, and $\Phi_{qq}(q, e) \leq 0$. The first-order properties ensure that a higher quality in bid is more likely to guarantee good performance of uncertain satisfaction, whereas a lower quality may lead to dissatisfaction. Similarly, a higher effort stochastically increases (decreases) the degree of satisfaction (dissatisfaction). The decrease of the expected uncertain satisfaction in decreasing quality is quicker than its increase in increasing quality. For effort e, the concavity of Φ has similar implications. Therefore, the second-order assumptions imply that the expected satisfaction is more sensitive to low quality and low effort.

Note that the bidder decisions on q and e still satisfy Lemma 1. Similar to the analysis in the base model, the bid price can be characterized as $b^*(\theta) = c(q^*(\theta),\theta) - \alpha \cdot \Phi(q^*(\theta), e^*(\theta)) + g(e^*(\theta)) + \int_\theta^{\bar{\theta}} c_\theta(q^*(t),t) \cdot \left(\frac{1-F(t)}{1-F(\theta)}\right)^{n-1} dt$.

Then we can immediately show the following result.

Proposition 9. *When the outcome of promised quality in bid is certain, the promised quality and information rent are both greater than those in the scenario of uncertain performance when the reference role is dominant.*

In the base model, when the performance of promised quality is uncertain and the reference role dominates, the expected satisfaction decreases in the promised quality. Thus, compared with the case when the enhancement role is dominant, the optimal mechanism under dominant reference role decreases both the promised quality and information rent. Proposition 9 suggests that when the performance of promised quality is certain, bidders offer higher promised quality compared with those in an auction of uncertain performance of promised quality under dominant reference role. This phenomenon occurs because promised quality without uncertainty generates an incentive on uncertain satisfaction ($\Phi_q > 0$), which incentivizes suppliers to leave more aggressive quality in their bids. Similar phenomena can be observed in many commercial practices. Manufacturers or service providers often highlight the measurable qualities of products or services in their advertisements or biddings. These actions usually exert positive influences on the buyer's belief of a higher probability of ex post satisfaction. Thus, compared with the auction of uncertain performance of promised quality with dominant reference role, bidders also increase their information rent by higher promised quality when the outcome of promised quality is certain. Similar to the base model, we also prove that $\alpha = 1$ and $s(q) = V(q)$ in the efficient mechanism, and $\alpha = 1$ and $s(q) = V(q) - D(q)$ in the optimal mechanism.

6.2 Asymmetric Effort Cost

In many practical scenarios, suppliers share similar production costs but may differ from each other in after-sales services and their unobservable efforts. Thus, we consider the scenario where suppliers have different costs of exerting their efforts to achieve the promised quality. Specifically, we introduce a parameter ξ to denote the different types of suppliers in effort cost $g(e, \xi)$, and ξ_i of bidder i is independently and identically distributed over support $[\underline{\xi}, \bar{\xi}]$ with distribution J and density j. We further assume that $g_{e\xi} > 0$, $g_{ee\xi} \geq 0$, and $g_{e\xi}(e, \xi) \cdot J(\xi)/j(\xi)$ increases in ξ, which is similar to the assumptions for $c(q, \theta)$ in the base model. Theoretically, the extended model involving multidimensional bids (indirect auction) is an extension of that of direct auctions with moral hazards. Essentially, the private information (type) in the classic direct auction mechanism is the effort efficiency (e.g., Laffont and Tirole 1987, McAfee and McMillan 1987). Considering that the type is effort efficiency, we assume that the promised quality as a function of effort, $q = \varphi(e)$, is natural, where $\varphi(.)$ is increasing and concave. Thus, its inverse $\varphi^{-1}(q)$ exists and the final performance of quality $\tilde{q}(\varphi(e), \varepsilon)$ is random. Other assumptions are similar to those in base model. As such, the expected revenue of bidder (type ξ) under the bid ($b(\xi)$, $q(\xi)$) is, where $Pr(win|b, q)$ is the winning probability, $U_s(b(\xi), q(\xi)|\xi) = [b - g(\varphi^{-1}(q), \xi) + \alpha \cdot \Lambda(q)] \cdot Pr(win|b, q)$.

The expected social welfare is $W(q) = V(q) - g(\varphi^{-1}(q), \xi_{(1)}) + \Lambda(q)$. We present the following proposition, and the superscript "*E*" represents the scenario where the private information (type) is effort efficiency.

Proposition 10. *When the performance of promised quality is uncertain and the type is effort efficiency ξ, the bidding price is $b^{E*}(\xi) = g(\varphi^{-1}(q^*(\xi)), \xi) - \alpha \cdot \Lambda(q^*(\xi)) + \int_{\xi}^{\bar{\xi}} g_{\xi}(\varphi^{-1}(q^*(t)), t) \cdot \left(\frac{1-J(t)}{1-J(\xi)}\right)^{n-1} dt$. The efficient mechanism is $s^E(q) = V(q) + (1 - \alpha) \cdot \Lambda(q),\ \forall \alpha \in [0, 1]$. The optimal mechanism is $s^E(q) = V(q) - D^E(q) + (1 - \alpha) \cdot \Lambda(q),\ \forall \alpha \in [0, 1]$, where $D^E(q) = \int_l^q [J(q_0^{-1}(s))/j(q_0^{-1}(s))] \cdot g_{e\xi}(\varphi^{-1}(s), q_0^{-1}(s)) \cdot \varphi_q^{-1}(s) ds$, and $q_0(\xi)$ maximizes $\{W(q(\xi)) - g_{\xi}(\varphi^{-1}(q(\xi)), \xi) J(\xi)/j(\xi)\}$.*

Unlike the result in base model, we find that the buyer can maximize her expected profit with any $\alpha \in [0, 1]$. In contrast to the base model where suppliers have different production cost types, the information rent is now directly related to the effort cost $g(e, \xi)$. However, unlike the direct mechanism, our model is an indirect mechanism with multidimensional bids, as the agent bids on both quality and price. As in McAfee and McMillan (1987), we observe the same phenomenon that the winner with the better type has less effort distortion, and the most efficient bidder has no distortion. The unique feature of the current extension model is that the effort is synchronized with promised quality. As such, the buyer can infer the effort from the observable promised quality, and distort the effort by using the scoring rule. Specifically, the buyer can now introduce any portion of the expected satisfaction $\Lambda(q)$ into the scoring rule. Accordingly, the bid price b accommodates any risk-sharing portion α before the realization of contingency. In summary, we observe that the promised quality in multidimensional auctions reconciles adverse selection and moral hazard in our setting.

7. Conclusion

In service procurement, promised quality and the supplier's unobservable effort are crucial drivers, usually together, of the buyer's *ex post* satisfaction. In this study, we explore a multi-attribute procurement mechanism by incorporating uncertain satisfaction. The buyer first initiates a scoring auction to award the contract to the winner whose bid scores the highest relative to competing bidders. Then, the winner exerts effort to increase the buyer's satisfaction, and the contingent transfer detailed in the *ex-ante* contract is realized based on *ex-post* assessment of the project.

We find that bidders jointly optimize the promised quality and effort before submitting the bid price. This finding is a generalization of the separation property in multidimensional auctions without satisfaction concern. Further, when the reference role of promised quality is dominant, the suppliers will submit lower promised quality in bid than when the enhancement role is dominant. The incorporation of satisfaction risk leads to several intriguing findings and insights. We find that it is crucial to classify the type of a buyer's satisfaction function, in terms of marginal contribution of promised quality and effort, as either quality sensitive or effort sensitive. When the scoring rule in the efficient mechanism (social surplus maximization) is compared to the one in the optimal mechanism (buyer utility maximization), the promised quality is always distorted downwardly. However, the effort level is distorted upward when the buyer is effort sensitive but downward when the buyer is quality sensitive. In the optimal mechanism, the buyer should use less distortion with a dominant reference role of promised quality compared with a dominant enhancement role, in response to anticipated lower promised quality. Further, we prove that the optimal mechanism requires a unique reserve score to exclude undesirable bidders who would cause negative utility for the buyer if they won the bid. An immediate implication is that neither reserve quality nor reserve price alone is sufficient to screen the undesired suppliers.

To further explore the impacts of uncertainty on our results, we studied two types of uncertainty with additive relationships between bidder behaviors and uncertainty. We consider both linear and nonlinear satisfaction functions and find that under certain conditions, both buyer and supplier can benefit from increasing uncertainty, which achieves a Pareto improvement. In particular, under linear satisfaction, promised quality and effort remain unchanged with uncertainty, while the buyer's expected utility increases in uncertainty when both mean and variance of the uncertainty increase but remains unchanged when only variance of uncertainty increases. Under nonlinear satisfaction, the impact of uncertainty depends on the types of uncertainty, two roles of promised quality, and the marginal contributions of promised quality and effort on satisfaction.

The multi-attribute auction combined with the PBC contract opens several promising avenues for potential future research. To begin with, our study poses some testable empirical questions which call for formal empirical investigation. Quantifying the cost saving and quality improvement from implementation of the PBC contract would allow us to better understand the economic value of this purchasing policy. Further, extending our two attributes auction framework to a more general setting would also be a potentially fruitful research direction for future scholars.

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Notes

[1]For exposition, we use bidders and suppliers interchangeably in the remainder of the manuscript.
[2]This is because that the promised quality is of concrete input cost, a higher investment is more likely to achieve a higher performance.
[3]To illustrate the result of Proposition 4, consider $v(q) = q^{\frac{2}{3}}, c(\theta,q) = \theta \cdot q, \theta \sim U[\underline{\theta},\bar{\theta}], \lambda(\Delta q) = \mu \cdot (1 - exp(-\Delta q))$ $(\mu > 0)$, $\Delta q = re - (1-k)q + \varepsilon(r \geq 0, k \geq 0), \varepsilon \sim U[a,b](0 < a \leq b)$, and g(e) = e^2/2, thus we have $W(q,e) - \frac{c_\theta(q,\theta)F(\theta)}{f(\theta)} = q^{\frac{2}{3}} - (2\theta - \underline{\theta}) \cdot q + \mu + \frac{\mu}{b-a}[exp((1-k)q - re - b) - exp((1-k)q - re - a)] - e^2/2$. We obtain ($q_0(\theta)$, $e_0(\theta)$) by solving the first-order conditions and derive the optimal scoring rule correspondingly. [Correction added on 11 January 2019, after first online publication: in the fifth line of Note 3, '$(2\theta - 1(\underline{\theta})$' was changed to '$(2\theta - \underline{\theta})$'.]
[4]We thank the anonymous reviewer who encouraged us to investigate along this direction.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1: Proofs.